Encoding Relation Requirements for Relation Extraction:
A Semantic Loss Perspective

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Abstract

Identifying relationship between entities is crucial for knowledge base population, question answering and etc. Most existing relation extractors make predictions purely based on the input natural language text, and ignore the argument type and cardinality constraints required by each relation. In this paper, we propose to format these constraints into propositional logic, and incorporate them to existing relation extractors by introducing a semantic loss. Our method does not introduce extra cost to the prediction phase and is plug-and-play for most existing relation extraction models. Experiments on both English and Chinese datasets show that our method improves the base model by a clear margin.

1 Introduction

Relation extraction (RE) aims at identifying relationship between entity pair from raw text, and its success can benefit many knowledge base (KB) related tasks like KB population, question answering (QA) and etc (Suchanek et al., 2013).

In the literature, RE is usually investigated in the distant supervision (DS) paradigm, where datasets are automatically constructed by aligning existing KB *(subject, relation, object)* triples with a large corpus, and considering sentences containing the subject and object entity in a triple as evidence for the corresponding relation (Mintz et al., 2009). To alleviate the sentence level noise in the automatically constructed dataset, RE is often considered in the multi-instance learning (MIL) framework where all the sentences containing the target subject and object are packed into a ***sentence bag***, and relation extractors take in these sentences to predict the relation for this entity pair. In this framework, the best-performing extractors are the ones based on neural networks (Zeng et al., 2015; Lin et al., 2016; Zeng et al., 2018). Apart

from representation learning or denoising, Ye et al. (2017) further models the co-occurrence tendency between relations via learning to rank.

While also focusing on the properties of relations, we, on the other hand, consider the constraints required by each relation. Take the relation *Capital* for example, it expects its subject to be a country and its object to be a city. And in most cases, it also expects a city to be the capital of one country only. These kinds of constraints can help us identify inconsistent predictions and thereby improve the extraction performance.

However, properly utilizing these constraints is non-trivial, since many KBs do not have a well-defined typing system or a cardinality specification for target relations. Chen et al (2014) deals with this challenge by automatically collecting relation pairs that have the same subject or object type to implicitly capture the type constraints, and relations that can have multiple subjects (or objects) given a specific object (or subject) to capture cardinality constraints. Then, they use integer linear programming (ILP) to resolve the predictions that are inconsistent regarding the constraints. However, since ILP operates at the post-processing phase and needs an adequate number of predictions to correct results, their method typically requires more time during prediction, and could not be applied to online applications.

To simplify the prediction procedure, we propose to incorporate these constraints by introducing a semantic loss to penalize inconsistent predictions during training. Specifically, we consider the type and cardinality constraints as propositional logic constraints, and use the semantic loss framework (Xu et al., 2017) to convert them into a loss. Compared to other methods of enforcing logical constraints like the teacher-student network (Hu et al., 2016) that relies on fuzzy relaxation of the constraints, semantic loss possesses the precise

meaning of the constraints and is fully differentiable since it directly uses the predicted probability to construct the loss. In this way, the base model is encouraged to find more textual clues when detecting conflicts, which leads to better prediction ability of the model, and the prediction phase incurs no extra costs. Further, since we only add a loss term to the base model, our method is plug-and-play for most relation extraction models.

We conduct experiments on both English and Chinese datasets, and the experimental results show that our method can clearly improve the base model, and delivers comparable performance compared to the `ILP` method.

2 Our Approach

2.1 Base Model

While our method can be adapted to most existing relation extractors, in this paper, we take the neural relation extractor of Lin et al. (2016) as our base model, which is currently one of the most widely used extractor in `RE`. Specifically, it operates in the `MIL` framework, and uses convolutional neural network for sentence embedding. Then, an attention layer is used to selectively aggregate sentence embeddings into a sentence bag embedding, which is then fed to a softmax classifier to generate the predicted relation distribution.

2.2 Relation Constraints

Our relation constraints are similar to those used by Chen et al. (2014). Specially, our relation constraints are defined over each combination of two triples: $(subj_i, r_i, obj_i)$ and $(subj_j, r_j, obj_j)$. [1] We derive type constraints and cardinality constraints from existing KB to implicitly capture the expected type and cardinality requirements for the arguments of a relation.

Type Constraint If the subject (or object) set of relation r_i in KB has a large intersection with those of r_j, then we consider r_i and r_j to have the same expected subject (or object) type. We thereby assign relation pairs (r_i, r_j) into $\boldsymbol{C}^{ts}$ (or $\boldsymbol{C}^{to}$) if they have the same subject (or object) type, $\boldsymbol{C}^{tso}$ if the subject type of one relation is the same as the object type of the other. The idea is that, if the predicted relations of two triples require the same entity to belong to different types, then at least one of the predictions must be wrong.

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[1] We use $subj$, obj and r to denote subject, object and relation for entity pair, respectively, in the rest of this paper.

Cardinality Constraint Given a subject (or object), some relations should have only one object (or subject). For example, the relation *Capital* would expect only one object for a given subject. Following this observation, we assign relation r into $\boldsymbol{C}^{cs}$ (or $\boldsymbol{C}^{co}$) if it can have multiple subjects (or objects) for a given object (or subject).

Finally, we get 5 sub-categories of constraint sets $\boldsymbol{C}^{\phi}$, where $\phi \in \boldsymbol{\Phi} = \{ts, to, tso, cs, co\}$.

2.3 Incorporate Constraints for Training

In this section, we demonstrate our method of converting the relation constraints into a loss using the semantic loss framework (Xu et al., 2017). We also introduce a variant of our method to speed up the training process by sampling constraints.

Relation Constraint Loss Semantic loss is a general framework that can encode propositional logic constraints as a loss in a principled way.

Concretely, in our work, for each sub-category of constraint sets $\boldsymbol{C}^{\phi}(\phi \in \boldsymbol{\Phi})$, our semantic loss for the combination of the ith and j^{th} entity pairs in a batch is defined as:

$$L^s(\boldsymbol{C}^{\phi}, \boldsymbol{p}_{ij}^{\phi}) = -\log \sum_{\boldsymbol{x} \models \boldsymbol{C}^{\phi}} \prod_{k:\boldsymbol{x} \models X_k} p_{ijk}^{\phi} \prod_{k:\boldsymbol{x} \models \neg X_k} (1 - p_{ijk}^{\phi}) \tag{1}$$

where $\boldsymbol{C}^{\phi}$ is defined over variables $\boldsymbol{X} = \{X_1, ..., X_{|R|}\}$, each variable $X_m \in \boldsymbol{X}$ represents a specific relation, $|R|$ is the number of relations, $\boldsymbol{p}_{ij}^{\phi}$ is the predicted probability vector of $\boldsymbol{X}$ derived by Eq. 2, $\boldsymbol{x} \models \boldsymbol{C}$ refers to the assignment $\boldsymbol{x} = \{x_1, ..., x_{|R|}\}$ of variables $\boldsymbol{X}$ that satisfies the constraints in $\boldsymbol{C}^{\phi}$, and $k:\boldsymbol{x} \models X_k$ (or $k:\boldsymbol{x} \models \neg X_k$) refers to the indices k where x_k is set to true (or false) in assignment $\boldsymbol{x}$.

As for our type constraints, an assignment $\boldsymbol{x} \models \boldsymbol{C}^t$, $t \in \{ts, to, tso\}$, is derived from a relation pair $(r_i, r_j) \in \boldsymbol{C}^t$, which corresponds to a relation assignemnt to entity pair i and j. Specifically, $x_k \in \boldsymbol{x}$ equals 1 only when r_i or r_j is the kth relation. Relation pairs where $r_i = r_j$ are excluded.

As for our cardinality constraints, an assignment $\boldsymbol{x} \models \boldsymbol{C}^c$, $c \in \{cs, co\}$, is derived from a relation $r \in \boldsymbol{C}^c$, where entity pair i and j are assigned the same relation r. Specifically, $x_k \in \boldsymbol{x}$ equals 1 only when r is the kth relation.

For the combination of ith and j^{th} entity pairs in a batch, we use $\boldsymbol{p}_{ij}^t$ and $\boldsymbol{p}_{ij}^c$ in Eq. (2) to denote the probability vector $\boldsymbol{p}_{ij}^{\phi}$ for type and cardinality

$$L^s(\mathbf{C}^{to}, \mathbf{p}_{ij}^{to}) = -\log\Big(\prod_{k\in\{\text{city},\text{state}\}} \mathbf{p}_{i,jk}^{to} \prod_{k\in R-\{\text{city},\text{team}\}} (1-\mathbf{p}_{i,jk}^{to})$$
$$+ \prod_{k\in\{\text{city},\text{team}\}} \mathbf{p}_{i,jk}^{to} \prod_{k\in R-\{\text{city},\text{team}\}} (1-\mathbf{p}_{i,jk}^{to}) + \dots \Big)$$
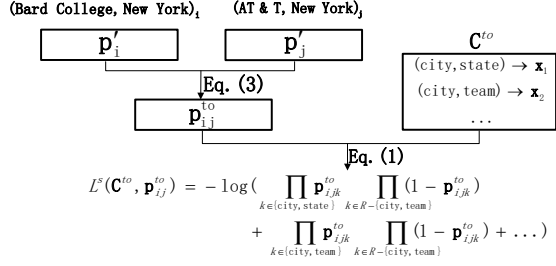
Figure 1: An Example of Semantic Loss Calculation for C^{to}

constraints in Eq. (1), respectively.

$$\boldsymbol{p}_{ij}^t = 1 - (1-\boldsymbol{p}_i') \odot (1-\boldsymbol{p}_j'); \quad \boldsymbol{p}_{ij}^c = \boldsymbol{p}_i' \odot \boldsymbol{p}_j' \quad (2)$$

where $\boldsymbol{p}_i'$ and $\boldsymbol{p}_j'$ represents the relation distribution outputs of our base model for the two entity pairs, $\odot$ is element-wise multiplier, $\boldsymbol{p}_{ij}^t (t \in \{ts, to, tso\})$ and $\boldsymbol{p}_{ij}^c (c \in \{cs, co\})$ denotes the predicted probability of variables $\boldsymbol{X}$ in the type and cardinality constraints, respectively.

In Fig. 1, we describe the semantic loss calculation for C^{to}. First, we get the relation distribution outputs $\boldsymbol{p}_i'$ and $\boldsymbol{p}_j'$ of our base model for the two entity pairs <*Bard College, New York*> and <*AT&T, New York*>, respectively, then we use Eq. 2 to get the predicted probability $\boldsymbol{p}_{ij}^{to}$ of variables $\boldsymbol{X}$, finally, we feed $\boldsymbol{p}_{ij}^{to}$ and $\boldsymbol{C}^{to}$ into Eq. 1 and get our semantic loss $L^s(\boldsymbol{C}^{to}, \boldsymbol{p}_{ij}^{to})$.

Training Procedure   Here we introduce the learning and optimization details of our model. Our objective function consists of two parts:

$$J(\theta) = J_{EN}(\theta) + J_{SL}(\theta) \quad (3)$$

where $J_{EN}(\theta)$ is the original cross-entropy classification loss, and $J_{SL}(\theta)$ is our total semantic loss.

Further, our total semantic loss is defined as:

$$J_{SL}(\theta) = \sum_{i<j} \sum_{\phi\in\Phi} \lambda^\phi m^\phi L^s(\boldsymbol{C}^\phi, \boldsymbol{p}_{ij}^\phi) \quad (4)$$

where $0 \le i < j < batch\_size$, λ^ϕ denotes the corresponding weight coefficient, m^ϕ is a 0-1 mask which is set to 1 when the two entity pairs satisfies the conditions of $\boldsymbol{C}^\phi$.

Note that, for each loss term, all the relation assignment pairs that satisfy the corresponding constraints are included. Therefore, minimizing these semantic loss terms actually increases the likelihood of all the relation predictions that satisfies our relation constraints.

During training, we iterate by randomly selecting a mini-batch from the training set until converge, and adopt the Adam optimizer (Kingma and Ba, 2014) to minimize the objective function.

Simplified Semantic Loss   In Eq. (1), for each entity pair combination, we need to calculate the semantic loss for every $\boldsymbol{x} \models \boldsymbol{C}^\phi$, which would be time-consuming since there are many relation assignments that satisfy the constraint set $\boldsymbol{C}^\phi$. However, among these assignments, only the gold standard assignment is the one that we desire. Therefore, we simplifies Eq. (1) by only including the gold relation assignment and a few randomly sampled consistent assignments as supplements. With this simplification, we wish to speed up the training process with only minor drop in performance.

3   Experiments

3.1   Experiment Settings

Datasets   We evaluate our approach on an English dataset and a Chinese dataset, which are proposed by Chen et al. (2014).

The English dataset is generated by mapping the triples in DBpedia (Bizer et al., 2009) to the sentences in the New York Time corpus. It has 51 relations, about 50k entity tuples, 134k sentences for training and 30k entity tuples, 53k sentences for testing.

The Chinese dataset uses a KB constructed by using the Infoboxes of HudongBaiKe, and aligns its triples to a corpus collected from four chinese economic newspapers. It contains 28 relations, about 60k entity tuples, 120k sentences for training and 40k tuples, 83k sentences for testing.

We do not use Riedel's dataset (Riedel et al., 2010), which is commonly used in RE, because Chen et al. (2014) have already mentioned that relation constraints does not work on that dataset.

Hyperparameters   We use grid search to determine the optimal parameters. Our base model use convolution window size 3, sentence embedding size 256, position embedding size 5 and batch size 50. The word embedding size is 50 and 300 for the English and Chinese dataset respectively. The loss weights for type constraints are 0.001 and 0.005 for the English and Chinese dataset respectively, and the weight for cardinality constraints is 0.0005 for both the English and Chinese dataset.

3.2   Experimental Results

Following previous work on RE, we use the precision-recall curve as our evaluation criterion. We compare our semantic loss method (SL) along with its simplified version (SL-simple) with the

base relation extractor (referred to as `Base`, see Sec. 2.1) and the `ILP` method (Chen et al., 2014).
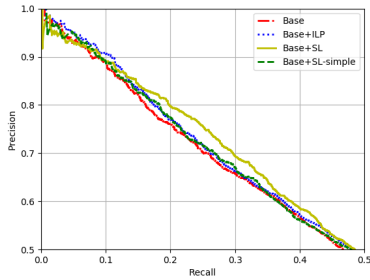

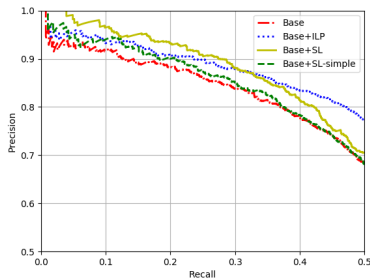Figure 2: Performance on English Dataset

Figure 3: Performance on Chinese Dataset

Compare with Base Model   As shown in Fig. 2 and Fig. 3, by encouraging the base relation extractor to make predictions that are consistent to our constraints, our `SL` method clearly improves the baseline relation extractor in both datasets.

Take <*Center For Responsible Lending, North Carolina*> and <*Meredith College, North Carolina*> as an example. `Base` outputs relations *Location* and *CoachedTeam* for these two entity pairs, and our `SL` model predicts *Location* and *State* instead. Note that *Location* requires its subject to be a place, and *CoachedTeam* expects its subject to be a team, so there exists a conflict between the two predictions. `Base` confuses *CoachedTeam* with *State* since many team names are the same as their state names, and these two relations sometimes share similar expressions in the contexts. However, with the help of relation constraints during training, our semantic loss term identifies the conflict and thus encourages the base extractor to focus more on the textual clues about relation *CoachedTeam*.

Compare with ILP Method   As shown in Fig. 2, in the English dataset, `SL` gets a comparable performance with `ILP` in the high precision

region, and performs better than `ILP` in the lower precision. We think the performance improvement comes from the fact that `SL` functions during training and `ILP` only acts as a post-processor. Therefore, `SL` can encourage the base model to find more textual clues when detecting conflicts, while `ILP` can only find the most probable relation assignment that satisfies the constraints based on the output scores of the base model, which will possibly drop some high-score predictions and thus still leave the correct relation with a low score.

As for the Chinese dataset, as shown in Fig. 3, we can see that `SL` obtains superior performance in the high precision region, but `ILP` performs better in the lower precision region. We think this is because the constraints in Chinese are more effective than that in the English dataset, which leads to more corrections of the `ILP` method. Therefore, since `ILP` tend to leave the predictions corrected by the constraints with lower scores, a large fraction of the correct predictions gather around the lower score region, which leads to higher precision of the `ILP` curve in the high recall region.

In practice, we usually require high-confidence extraction results, the performance of the high-precision region of the PR curve is more important than the low-precision one. Further, recall that different from `ILP`, `SL` does not introduce extra cost during prediction. These experiments indicate that `SL` method is more effective than `ILP` in practice.

Compare with Simplified Semantic Loss   We also show the performance of our simplified semantic loss in Fig. 2 and Fig. 3 (`SL-simple`). We can see that, while inferior to `SL`, `SL-simple` also improves `Base` by a clear margin, and it is also comparable to `ILP` in the English dataset. In our experiments, compared to the original `SL` method, `SL-simple` reduces the extra training time introduced by calculating the semantic loss by 7 times in the English dataset, and 3 times in the Chinese dataset, which has less constraints than those in the English dataset. This indicates that `SL-simple` acts as a good balance of the trade-off between extraction quality and extra training time.

4   Conclusion

In this paper, we introduced a semantic loss for `RE` to help resolve the conflicts to type and cardinality constraints among local relation predictions, which is adapted to most existing relation extrac-

tors. Our method does not bring extra cost during prediction, and the experiments show that our method consistently improves the performance of the base relation extractor by a clear margin.

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